An Adaptive Soft Calibration Technique for Thermocouples using Optimized ANN

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Abstract— **Design of an adaptive soft calibration technique for temperature measurement using Thermocouple by an optimized Artificial Neural Network (ANN) is reported in this paper. The objectives of the present work are: (i) to extend the linearity range of measurement to 100% of full scale input range, (ii) to make the measurement technique adaptive to variations in temperature coefficients, and (iii) to achieve objectives (i) and (ii) using an optimized neural network. Optimized neural network model is designed with various algorithms, and transfer functions of neuron considering a particular scheme. The output of Thermocouple is of the order of milli volts. It is converted to voltage by using a suitable data conversion unit. A suitable optimized ANN is added in place of conventional calibration circuit. ANN is trained, tested with simulated data considering variations in temperature coefficients. Results show that the proposed technique has fulfilled the objectives.**

Index Terms— **Artificial Neural Network, Calibration, Optimization, Thermocouple**

I. Introduction

Temperature plays an important role in all fields of natural science, including physics, geology, chemistry, atmospheric sciences and biology. Many physical properties of materials including the phase (solid, liquid, gaseous or plasma), density, solubility, vapor pressure, and electrical conductivity depend on the temperature. Temperature also plays an important role in determining the rate and extent to which chemical reactions occur. Thus, an accurate and precise measurement of temperature is very important. There is various contact type electrical temperature sensors used for the measurement of temperature. Thermocouple is one such commonly used sensor. Ruggedness and low power dissipation are the main two characteristics of Thermocouple which promotes its use over the other temperature sensors, like Resistance Temperature Detector and Thermistor. However in a Thermocouple, the problem of non linear response characteristics have made it difficult to use this sensor fully and restricted its use in terms of measurable range of input temperature.

In practice, this problem of nonlinearity is overcomed by using some calibration techniques. Even after calibration there may be some error, and the process of calibration is to be repeated whenever a thermocouple is replaced, which is time consuming and may demand for a change in hardware also. This increases the time requirement and effective cost of the instrument.

In [1], neural network is used to linearize a portion of full scale for temperature measurement using thermocouple. LabVIEW curve fit algorithm is used to linearise thermocouple in [2]. In [3], back propagation neural network is trained to linearise portion of output of Type K thermocouple and implementation on microcontroller is discussed. Linearization of thermocouple is discussed using B-spline support vector machine in [4]. In [5], least squares support vector regression machine (LS-SVR) is applied to non-linearity calibration of a thermocouple sensor. In [7], [10], linearization of thermocouple using look up table written on microcontroller is discussed. A method of linearising thermocouple using hardware circuit, and software using look up table is discussed in [6], [8], [9], [14]. In [11], Calibration of RTD and Thermocouple is discussed using the LabVIEW curve fit algorithm. A method to compensate thermocouple sensor non-linearity based on orthogonal polynomial basis functions neural network is presented in [12]. In [13], design of an intelligent technique for temperature measurement using thermocouple is designed and output is made adaptive of temperature coefficients.

Literature review suggests that the above papers have discussed various methods of linearization, but most of these methods are restricted to a portion of full scale of input range. Further, adaptation to variation in temperature coefficients is also not discussed, which means that the system needs to be repeatedly calibrated whenever thermocouple is changed. This paper aims at designing an intelligent calibration technique using optimized neural network to overcome the restriction of the above discussed works. This paper is an improvement over [13], where linearization of thermocouple for full scale, and adaptation of temperature coefficients was achieved with arbitrary neural network with two hidden layers. This paper proposes an improvement by optimization of neural network, in terms of neural network algorithm, scheme, and transfer function of neurons to achieve a optimized neural network.

The paper is organised as follows: After introduction in Section I, a brief description on thermocouple is given in Section II. The output of the thermocouple is of the order of milli volts; a brief discussion on data conversion is done in Section III. Section IV deals with the problem statement followed by proposed solution in Section V. Result and analysis is given in Section VI. Finally, conclusions and discussions in Section VII.

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II. THERMOCOUPLE

A thermocouple is a temperature-voltage transducer. It is a device made by two different wires joined at one end, called junction end or measuring end. The two wires are called thermo elements or legs of the thermocouple. The two thermo elements are distinguished as positive and negative ones. The other end of the thermocouple is called tail end or reference end as shown in Fig 1. The junction end is immersed in the environment whose temperature T_2 is to be measured, while the tail end is held at a different temperature T_1.

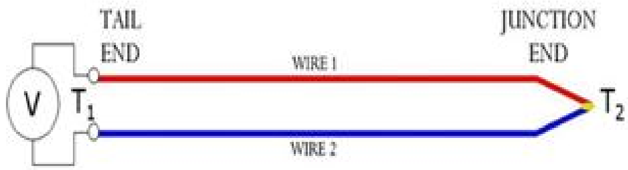

Figure 1. Schematic diagram of a thermocouple

Because of the difference in temperature between junction end and tail end, a voltage is measured between two thermo elements at tail end.

Approximately 300 different types of temperature measuring thermocouples have been identified and studied [15-17]. But, only a few types having the more favorable characteristics are used in general. There are eight types of thermocouples that have been standardized. Table-1 shows the list of standard thermocouples with its materials and ranges.

TABLE I. TYPES OF STANDARD THERMOCOUPLE

Sl. no	Type	Materials	Typical Range °C
1	T	Copper (Cu) vs Constantan	-270 to 400
2	J	Iron (Fe) vs Constantan	-210 to 1200
3	K	Chromel vs Alumel	-270 to 1370
4	E	Chromel vs Constantan	-270 to 1000
5	S	(Pt-10%Rh) vs Pt	-50 to 1768
6	B	(Pt-13% Rh) vs (Pt-6% Rh)	0 to 1820
7	R	(Pt-13%Rh) vs Pt	-50 to 1768
8	N	(Ni-Cr-Si) vs (Ni-Si-Mg)	-270 to 1300

Equation 1 illustrates the power series model used for J type thermocouples [15,16]

$$V = C_1(T_2 - T_1) + C_2((T_2 - 273)^2 - (T_1 - 273)^2)\mu V \quad (1)$$

where:

T_2 – Hot junction temperature of thermocouple in °C
T-$_1$ – Cold junction temperature of thermocouple in °C
C-$_1$ & C_2 – Coefficients depending on the materials used.

III. DATA CONVERSION UNIT

The block diagram representation of the proposed instrument is given in Fig 2.

In cold junction compensator the tail end is at ambient temperature and the temperature fluctuations at the tail end are tolerated; in fact the cold junction compensator produces a voltage equal to the thermocouple voltage between 0°C and ambient temperature, which can be added to the voltage of the thermocouple at the tail end to reproduce the voltage versus temperature relationship of the thermocouple [15], [18].

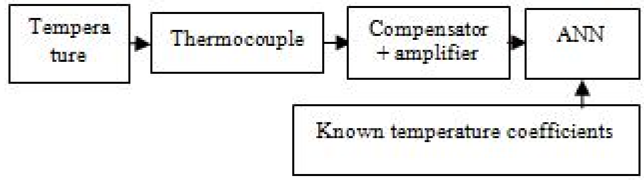

Figure 2. Block diagram of the proposed temperature measuring technique

A sketch of a thermocouple with cold junction compensation is reported in Fig 3.

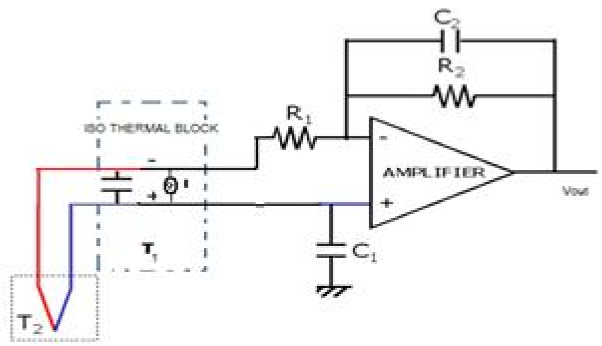

Figure 3. Data conversion circuit for thermocouple

IV. PROBLEM STATEMENT

In this section characteristic of thermocouple is simulated to understand the difficulties associated with the available measurement techniques. For this purpose, simulation is carried out using J type thermocouple. Eqn.1 is used to find the output voltage of thermocouple with respect to various values of input temperature considering particular values for coefficients. These output voltages are used as input to compensator and amplifier circuit and the final voltage is produced.

The MATLAB environment is used of and the following characteristics are found.

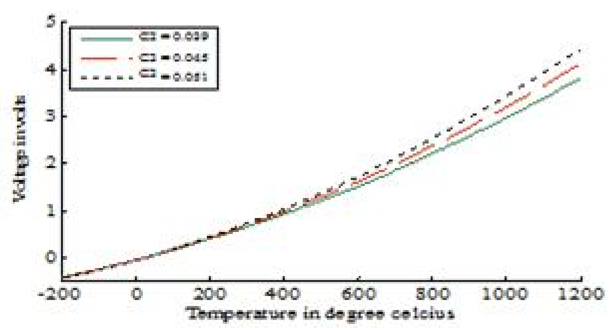

Figure. 4. Data converter outputs for variation of temperature and C_2 with C_1 = 60

Fig. 4 and Fig. 5, shows the variation of voltage with the change in input temperature for different values of coefficients.

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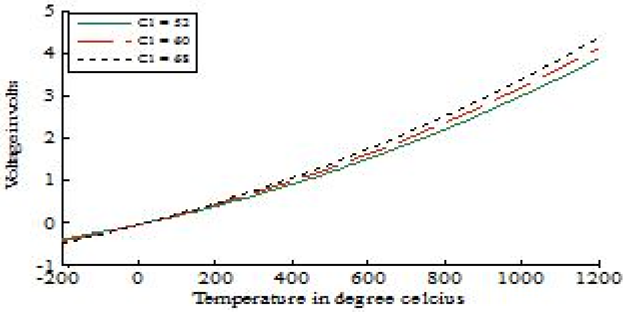

Figure 5. Data converter outputs for variation of temperature and C_1 with C_2 = 0.045

It has been observed from the above graphs (Fig 4 and Fig 5) that the output from the data converter circuit has a non linear relation. Datasheet of thermocouple suggests that the input range of 10% to 70% of full scale is used in practice as linear range. The output voltage also varies with the change in coefficients. These are the reasons which have made the user to go for calibration techniques using some circuits. These conventional techniques have a drawback that its time consuming and need to be calibrated every time a thermocouple is replaced. Moreover, the use is restricted only to a portion of full scale.

To overcome these drawbacks, this paper makes an attempt to design a temperature measuring technique incorporating intelligence to produce linear output and to make the system independent of coefficients using the concept of optimized artificial neural network.

Problem statement: given an arrangement for measurement of temperature consisting of Thermocouple in cascade with data converter circuit as shown in Fig.1, design an intelligent soft calibration technique using optimized neural network model and having the following properties:

i. Adaptive of variation in temperature coefficients C_1 & C_2

ii. Output bears a linear relation with the input temperature.

iii. Full scale input range can be measured.

iv. Achieve all the above using optimized ANN.

V. Problem Solution

The drawbacks discussed in the earlier section are overcomed by adding an optimized ANN model in cascade with data converter unit replacing the conventional calibration circuit. This model is designed using the neural network toolbox of MATLAB.

The first step in developing a neural network is to create a database for its training, testing, and validation. The output voltage of data conversion unit for a particular temperature, temperature coefficients is stored as a row of input data matrix. Various such combinations of input temperature, temperature coefficients, and their corresponding voltage at the output of data conversion unit are used to form the other rows of input data matrix. The output matrix is the target matrix consisting of data having a linear relation with the input temperature and adaptive of variations in temperature coefficients, as shown in Fig 6.

The process of finding the weights to achieve the desired output is called training. The optimized ANN is found by considering different algorithms in first step and then by varying the transfer functions of neurons in second step to find an optimized structure with minimum number of hidden layers subject to MSE less than the predefined value. MSE is the average squared difference between outputs and targets. Lower values of MSE are better. Zero means no error.

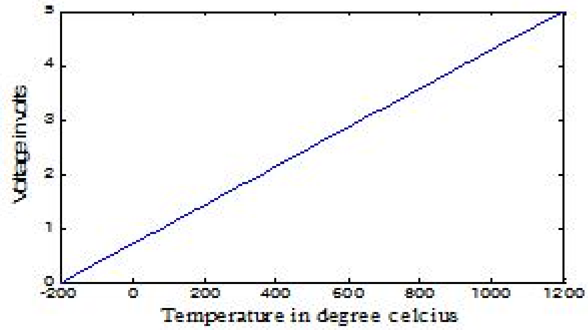

Figure 6. Target graph

Four different algorithms with back propagation scheme are used to find the optimized ANN in first step. These are Back Propagation (BP) trained by Ant Colony Optimization (ACO) [19 - 21], Back Propagation trained by Artificial Bee Colony (ABC) [22], [23], Back Propagation (BP) trained by Genetic Algorithm (GA) [24 - 26], and Back Propagation trained by Particle Swarm Optimization (PSO) [27], [28]. Training of ANN is first done assuming only one hidden layer. MSE values are noted. Hidden layer is increased to 2 and training is repeated. This process is continued up to 5 hidden layers. In all cases MSE are noted and shown in Table II. MSE's corresponding to different algorithms and number of hidden layers is shown pictorially in Fig. 7. Table II and Fig.7 very clearly shows that BP trained by PSO yields most accurate results. BP trained by PSO with 1 hidden layer is considered as the most optimized ANN for desired accuracy after first step.

Table II. Comparison Of Mse For Neural Network Models

Layers	BP_ ACO	BP_ ABC	BP_GA	BP_PSO
1	1.11E-2	9.95E-3	5.11E-3	**1.62E-3**
2	5.83E-4	2.99E-4	1.63E-4	8.55E-5
3	1.32E-6	8.66E-7	4.38E-7	1.85E-7
4	1.99E-9	9.26E-10	6.02E-10	3.01E-10
5	3.21E-11	1.08E-11	8.23E-12	5.57E-12

Different transfer functions of neuron are used in literature. In second step, training, testing, and validation are repeated with ten different transfer functions of neuron BP trained by ACO, the outcome of first step on the optimized ANN. BP_PSO with one hidden layer obtained in the first step. The effect of neuron TFs in terms of MSE are noted and tabulated in Table-2. Softmax TF is finally used in the optimized ANN based on the outcome of second step, as shown in the Table-III. Details of the optimized neural network is given in Table-IV

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TABLE III. COMPARISON OF DIFFERENT NEURON TRANSFER FUNCTION

Sl.no	Transfer function	MSE
1.	Tanh	6.32E-4
2.	Sigmoid	7.02E-4
3.	Linear Tanh	5.02E-4
4.	Linear sigmoid	4.11E-4
5.	Softmax	**9.99E-5**
6.	Bias	9.08E-4
7.	Linear	1.62E-3
8.	Axon	1.11E-4
9.	Tansig	2.81E-4
10.	Logsig	1.93E-4

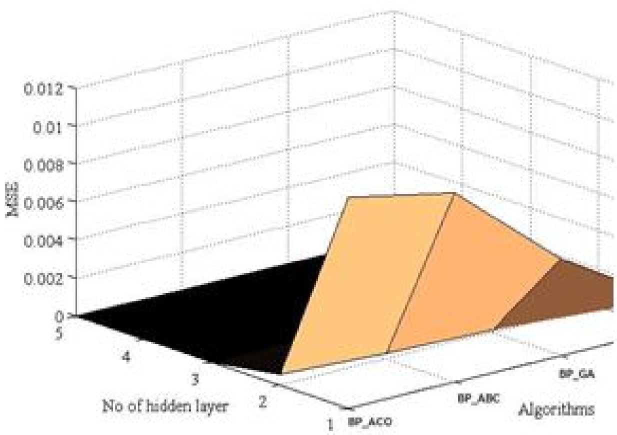

Figure 7. Mesh of variation of MSE with algorithm and hidden layer

TABLE IV. DETAILS OF OPTIMIZED NEURAL NETWORK MODEL

<table>
<tr><td colspan="5">Optimized parameters of the neural networks model</td></tr>
<tr><td colspan="2" rowspan="3">Database</td><td colspan="2">Training base</td><td>100</td></tr>
<tr><td colspan="2">Validation base</td><td>33</td></tr>
<tr><td colspan="2">Test base</td><td>33</td></tr>
<tr><td colspan="2">No of neurons in</td><td colspan="2">1st layer</td><td>9</td></tr>
<tr><td colspan="2" rowspan="2">Transfer function of</td><td colspan="2">1st layer</td><td>Softmax</td></tr>
<tr><td colspan="2">Output layer</td><td>Linear</td></tr>
<tr><td rowspan="3">Input</td><td></td><td>Temp</td><td>C1</td><td>C2</td></tr>
<tr><td>min</td><td>-210 °C</td><td>55</td><td>0.040</td></tr>
<tr><td>max</td><td>1200 °C</td><td>65</td><td>0.050</td></tr>
</table>

VI. RESULTS AND ANALYSIS

The optimized ANN is subjected to various test inputs corresponding to different values of temperature coefficient, all within the specified range. For testing purposes, the range of temperature is considered from -210°C to 1200°C, range of C_1 is 55 to 65, and C_2 is 0.040 to 0.050. The temperatures measured by the proposed technique corresponding to sampled test inputs are tabulated in table V. Table V suggests that measured temperature are almost same as actual temperature. Root mean square of % error for 32 different simulated testicles is 0.1082. It may be noted that the test conditions in table V are different from the training data set.

VII. CONCLUSIONS AND DISCUSSIONS

Available reported works in [1-14], have discussed different techniques for calibration of temperature measurement using thermocouple. These techniques are not adaptive of variations in temperature coefficients. Hence, repeated calibration is required for any change in temperature coefficients with change in thermocouple. Further, most reported works have not utilized the full scale of input range. Moreover, in all the referred reported papers, wherever neural network is used, the structure has been selected without any justification.

In comparison to these, the proposed measurement technique achieves linear input output characteristics for full input range of temperature. All these have been achieved by using an optimized ANN. Optimization is done with respect to algorithms, and TFs of neuron to find an ANN model with less number of hidden layers, Results shows the proposed technique has found to have achieved the desired MSE with only one hidden layers. This is in contrast to an arbitrary ANN in most of the earlier reported works. Results in table V show that objectives are achieved satisfactorily**.**

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TABLE V. RESULTS OF PROPOSED TECHNIQUE WITH SIMULATED DATA

Actual temperature in ^{o}C	C_1	C_2	o/p of data conversion unit in V	ANN o/p in V	Measured temperature in ^{o}C	% Error
-210	55	0.040	-0.3215	0.001	-209.998	0.0010
-210	58	0.041	-0.3410	0.000	-209.999	0.0005
-110	60	0.042	-0.2200	0.3545	-110.126	-0.1145
-110	62	0.043	-0.2276	0.3546	-109.963	0.0336
-60	64	0.044	-0.1537	0.5318	-59.993	0.0117
-60	65	0.045	-0.1560	0.5317	-59.911	0.1483
30	64	0.046	0.0096	0.8509	29.911	0.2967
30	63	0.047	0.0095	0.8509	29.909	0.3033
90	62	0.048	0.1270	1.0630	89.908	0.1022
90	61	0.049	0.1252	1.0640	90.032	-0.0356
180	60	0.050	0.3150	1.3826	179.98	0.0111
180	59	0.049	0.3097	1.3822	179.89	0.0611
220	58	0.048	0.3941	1.5250	220.13	-0.0591
220	57	0.047	0.3871	1.5252	220.08	-0.0364
300	56	0.046	0.5663	1.8083	299.93	0.0233
300	55	0.045	0.5558	1.8081	299.88	0.0400
410	56	0.044	0.8424	2.1973	409.16	0.2049
410	57	0.043	0.8496	2.1965	409.02	0.2390
560	58	0.042	1.2915	2.7291	559.91	0.0161
560	59	0.041	1.2990	2.7296	559.98	0.0036
630	60	0.040	1.5282	2.9802	630.03	-0.0048
630	61	0.041	1.5574	2.9793	630.16	-0.0254
720	62	0.042	1.9013	3.2990	720.65	-0.0903
720	63	0.043	1.9366	3.2980	720.24	-0.0333
840	64	0.044	2.4416	3.7233	839.91	0.0107
840	65	0.045	2.4860	3.7231	839.21	0.0940
900	64	0.046	2.7366	3.9362	900.25	-0.0278
900	63	0.047	2.7333	3.9363	900.38	-0.0422
1130	62	0.048	3.8136	4.7502	1129.87	0.0115
1130	61	0.049	3.8171	4.7522	1130.15	-0.0133
1200	60	0.050	4.1860	4.9985	1199.25	0.0625
1200	59	0.049	4.1093	4.9899	1198.75	0.1042

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